Issues in Information Systems
Volume 25, Issue 4, pp. 158-172, 2024

DOI: https://doi.org/10.48009/4_iis_2024_113

AI implementation in big data: Shaping data analysis for business decisions

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Abstract

This research measures the association of Big data and AI, focusing on how these technologies enhance various types of data analysis critical for business decision-making. By analyzing a substantial dataset of data scientists and analysts from countries of the world, the study identifies patterns and relationships between different types of Big data, AI techniques, and the resultant data analyses. It aimed to establish the relationship between big data and artificial intelligence and the relationship between artificial intelligence and the types of data analysis for the strategies or decision-making that companies require. This research attempts to understand better how companies make decisions about how or what types of analysis are most appropriate, incorporating artificial intelligence to analyze the various data structures generated in companies. A sample of 3,574 data science and analytics specialists from countries was analyzed from a database https://www.kaggle.com. The results indicated a relationship between Big data and intelligence, as well as between artificial intelligence and different types of data analysis. 66% of data mining artificial intelligence algorithms mainly were implemented for structured data. Data mining artificial intelligence algorithms mostly analyzed 37% of diagnostic data types. 3% of prescriptive data types were analyzed mainly by text-mining artificial intelligence algorithms.

Keywords: Big data, artificial intelligence, data analysis, descriptive, diagnostic, predictive, prescriptive

Introduction

The firms report a high return on investment after adopting artificial intelligence, which provides future direction to the new organizations aiming to maximize profits (Mendis & Dharmasiri, 2019). Businesses, by their nature, are constantly striving for this, monetizing all aspects of their operations to maximize profits and better serve their shareholders and stakeholders (Wixom, 2014). Descriptive and diagnostic tools are more efficient in assessing the firm's current and future needs, which is linked to better decision-making and returns (Shabbir & Anwer, 2015). Data visualization improves the possibility of representing information and details in an organized manner, leading to greater efficacy (Ridzuan et al., 2022). The four types of analytics: descriptive, diagnostic, predictive, and prescriptive influence the decision-making process of the firms, affecting their returns and success (Ingram et al., 2014). AI's most prominent benefit is predicting future business outcomes based on a more authentic analysis of the historical data (Rich, 2018). This new technology aims to maximize the competency of business leaders and professionals to increase the accuracy of data that assists the organization in making more reliable and better decisions.

Companies integrate AI into the performance of different analytics, including diagnostic, descriptive, predictive, and prescriptive, with the ability to retrieve required data from databases (Diabagate, Azmani, & Harzli, 2014). Unnecessary delays in collecting relevant information related to the issue can be accessed easily in no time with AI, resulting in effective decision-making. These benefits have helped organizations perform more effective market analyses to find potential customers and their preferences and make the right decisions regarding expansion. The availability of the customer's data in massive databases has also maximized the chances of retaining old customers and hiring new ones, supported by descriptive and diagnostic analytics. AI has also provided the customer's relationship management tool for analyzing the existing customer base, seeking information about their changing preferences and future expectations, thus assisting firms in better customer strategy decisions (Bolland & Lopes, 2018). Adopting AI has helped organizations achieve their goal of sales generation and revenue maximization (Hong et al., 2021). They have applied automated techniques for collecting the relevant data, helping them maximize profits. Another benefit of AI is adopting more advanced marketing analytics, improving brand awareness and the company's position. AI allows prescriptive analytics to be more accurate in determining solutions for low customer turnover or reduction in sales (Sariolghalam et al., 2010).

Performance assessment is another advantage of AI tools that promotes integrity and eliminates the chances of human errors. This technology has maximized the opportunities of making employees' performance data more transparent. The role of manual tasks is also reduced, posing the challenges of evaluating staff performance. The reduction in errors and accuracy of AI allows companies to increase efficacy. A greater understanding of predictive analytics enhances their competency in making forecasts about the transportation industry, such as sales, returns, and changing profit figures (Davenport & Ronanki, 2018). Research studies on AI suggest the need to learn about modern and advanced processes to avoid delays and complications. Key benefits of AI include simplicity, faster results, and cost flexibility (Ferrero et al., 2021). Data storage and cloud management remain essential features that organizations need. Opportunity management is another feature that maximizes a firm's competency in growing sales and attracting new potential customers. Lead management optimizes operations and assists the sales team in making smarter decisions (Hass, 2021). Pre-integrated AI apps provide automatic access to the cloud and improve data efficiency (Hecht et al., 2019).

Big Data

Big Data is based on the Volume, Speed, and Variety with which the data will be generated. Volume refers to the size of the data sets, velocity refers to the speed at which data sets are created, and variety refers to the diversity of data types (McAfee & Brynjolfsson, 2012). Big Data includes three data types: structured, semi-structured, and unstructured (Rose, 2016). According to Etchings (2017), structured data is more straightforward to analyze, while unstructured data is more complex; both structures play an essential role in practical data analysis (Taylor, 2018). Structured data are sets of data that are stored in relational databases (Sherpa Software, 2013). The decision-making process, supported by Big Data, helps improve the productivity of organizations and makes them capable of being competitive in the market. Poleto et al., (2015), indicate that corporate decision-making is characterized by two types of elements: organizational and technical. The elements of organizational decision-making are related to the day-to-day functional life of organizations.

Artificial Intelligence

Procurement practices that lead to implementing AI projects include establishing an appropriate level of control, reducing risks, and improving the adaptability of AI projects in organizations (Rich, 2018). Procurement arrangements like properly aligning staff and establishing alliances with supply chain activities improve the probability of successful implementation of AI (Shabbir & Anwer, 2015). Project management practices are aimed at making staff responsible for using their tactical skills to make the best decisions based on the perceptions of clients and vendors. Integration of best practices of procurement and management arrangements in artificial intelligence projects allows the handling of risks automatically (Tamers et al., 2020). Data mining helps to control, optimize, manage, examine, investigate, plan, predict, submit, negotiate, or make business decisions (Molina-Felix, 2002). Machine learning is another advanced type of data analysis in which AI-based algorithms process extensive data sets faster than any other form of data modeling (Rouse, 2016). Machine learning is an advanced artificial intelligence data analysis that processes large data sets more quickly through data modeling (Rouse, 2016). Machine learning analyzes data from past experiences to solve problems (Alpaydin, 2020).

Data analysis is necessary to obtain valuable information from unstructured data (Olguín-Gallardo, 2018). Deep Learning techniques and neural networks have produced essential advances in Artificial Intelligence worldwide in recent years (Vázquez & Constable, 2019). The recent successes of deep learning techniques in solving many complex tasks by learning from data have created much excitement and significance in the research community (Tyrsa et al., 2017).

Type of Data Analysis

Business decisions are dependent on four types of analytics: descriptive analytics, diagnostic analytics, predictive analytics, and prescriptive analytics. The central goal of these analytics is to assist business leaders in making realistic and better decisions that contribute to improved efficiency. More effective decision-making focuses on better financial position, improved customer retention, product/service revenue creation, and highly competitive advantage (Meissner et al., 2021). Leaders' competency in analyzing data efficiently enables businesses to conclude, make future predictions, and share actionable insights to guarantee better performance in the future. Business professionals need knowledge of data analytics to access data and formulate strategies leading to effective decisions. Data analytics knowledge is more important for analyzing markets and industries and improving companies' products. Financial managers use modern tools to forecast companies' financial trajectories, which leads to well-informed decisions. Marketers use customer data, performance data, and industry trends to plan better marketing strategies linked with high returns.

Descriptive Analysis

Descriptive analytics aims to pull trends from raw data and explain what is happening. Leaders use this technique to visually represent sales, forecasts, and projections. The goal is to present historical data in an organized manner that helps understand business changes. Analysts employ two essential methods for performing descriptive data analysis: data aggregation and mining, which are applied to discover historical data. This involves the collection of historical data, organization, and appropriate presentation. Inferences and predictions can be drawn from the historical data that guide future actions. Descriptive analytics uses math and statistical tools such as arithmetic, averages, and percentages to present well-organized data. Visual tools such as line graphs, bar charts, and pie charts are standard methods of displaying the collected information. The data mining phase is used to determine patterns and trends that are presented in an understandable way to the audience. It is also essential to find if the results of the descriptive analysis show a new trend, especially with natural variability in the data, in this case, statistical analysis is used to find if results deviate from the norm (Kozioł-Nadolna & Beyer, 2021).

Diagnostic analytics examines the data or the content to answer the questions related to the business. It applies various techniques, including data discovery, drills down, data mining, and correlations. The goal is to find the exact cause of the issue for resolving it. The purpose is to determine the root cause of the trend's occurrence using information from descriptive analytics (Gartner, 2018). Diagnostic analytics is not limited to illustrating trends and patterns for identifying causes; factors that drive trends and help companies understand variations in business performance or customer behavior are highlighted (Ridzuan et al., 2022).

Predictive Analytics

Predictive analytics is equally important in businesses for suggesting future recommendations based on the existing limitations. This is an effective tool for maximizing possibilities of effective decision-making. Historical data is analyzed to inform about different aspects of the business, the leaders, and concerned personnel. More realistic goals are set with adequate planning and performance management, avoiding risks (Meissner et al., 2021). Predictive analytics uses various techniques, such as data mining and statistical modeling, to determine the mathematical relationship between the variables. The machine learning algorithm is also applied to the classification of regression and clustering techniques, leading to accurate decisions related to business progress. Machine learning algorithms also fill in the missing data, thus maximizing the capacity to make the right decision. Machine learning is deep learning that constructs human neural networks as layers of nodes learned through specific process areas and networked into an overall prediction.

Prescriptive Analytics

Prescriptive analytics tells what will happen and what actions should be taken to improve business operations. This methodology helps executive managers, executives, and operation employees to make the best decisions based on the available data (Bolland & Lopes, 2018). Prescriptive analytics acquires data from descriptive and predictive analytics and offers solutions to improve the business. This complex stage demands specialized knowledge analytics to enhance day-to-day business operations. The leaders and the executives use it to make recommendations by relying on several statistical techniques and tools. It extends beyond the capabilities of machine learning to determine what results can be achieved (Davenport & Ronanki, 2018). In prescriptive analytics, business rule algorithms, computational modeling, and machine learning are used to make accurate and well-informed choices (Hong et al., 2021). Predictive analytics is about making forecasts related to the firm's future sales, profitability, and performance. Lopes et al., (2020). The process involves solving complex commutations to make accurate estimates about the future (Lopes et al., 2020).

Problem

Traditional data analytics methods have become irrelevant to modern business practices because they require more time and energy (Hong et al., 2021). Firms face fierce competition from rival firms, which reveals the need to adopt more relevant technology to maximize business returns (Tinoco et al., 2021). The decision of firms to invest in AI is based on their ability of deriving immediate returns. It is also seen as a significant way of shifting from companywide programs to customer segmentation (Gartner, 2018). Diagnostic analysis demands proper attention for gaining an understanding of the situation in depth therefore artificial intelligence promotes diagnostic skills. Leaders manage to deep-dive into data to search for insights and explore the reasons behind the results (Hong et al., 2021). It is important to study prescriptive analysis for better decision making of companies (Nemetha et al., 2018). There is a need for aligning functional strategies with corporate strategies saving time and effort for the business leaders (Bănărescu, 2015).

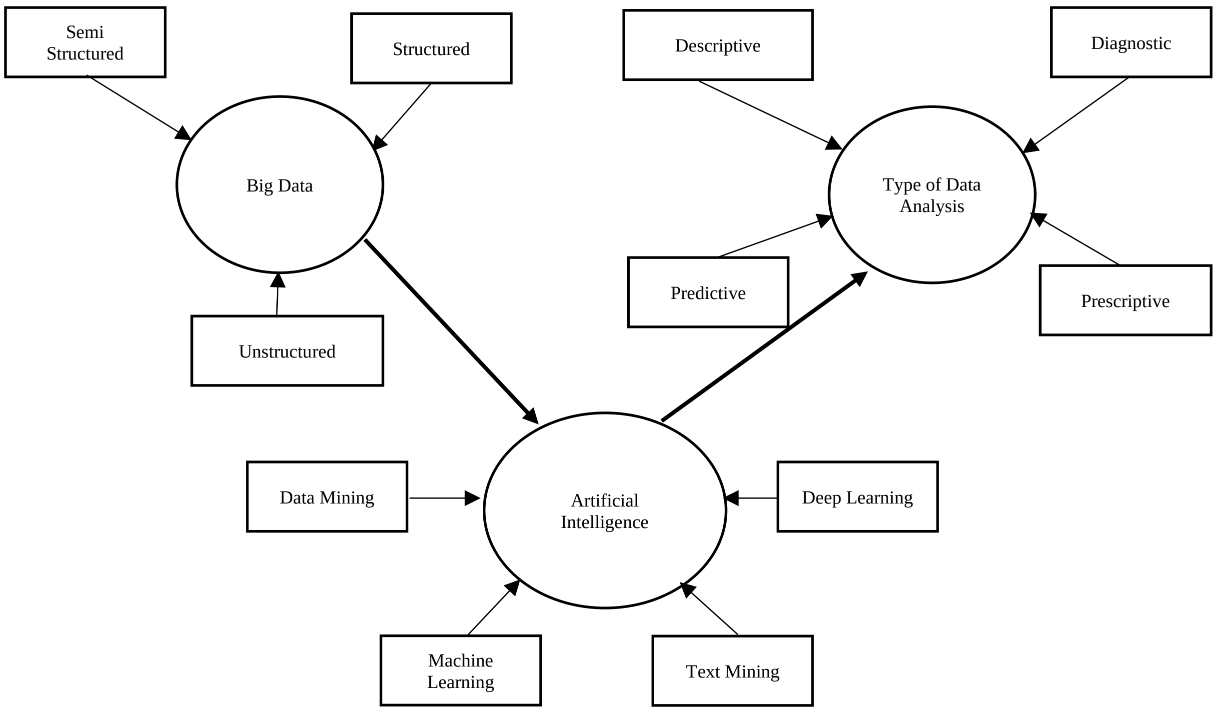

Figure 1: Model Established by Researchers

The model in Figure 1 includes three main variables: Big Data, Artificial Intelligence, and Type of Data Analysis. Each variable has several indicators. Big Data is categorized into three types based on the structure of the data: Structured refers to data organized in a defined manner, typically in rows and columns, making it easily searchable by algorithms. Examples include databases and spreadsheets. Semi-Structured refers to type of data does not follow a strict structure but contains tags or markers to separate data elements. Examples include JSON, XML files, and emails. Unstructured refers to data that lacks a predefined format or organization, making it difficult to collect, process, and analyze. Examples include text documents, videos, and social media posts.

Artificial Intelligence (AI) encompasses various techniques used to analyze big data: Data mining that involves extracting patterns from large datasets using statistical methods, machine learning, and database systems. Machine Learning that is subset of AI involves training algorithms on data to enable them to make predictions or decisions without explicit programming. Text mining focuses on extracting useful information from text data using natural language processing (NLP) and other techniques. Deep learning is subset of machine learning uses neural networks with many layers (deep networks) to model complex patterns in large datasets. The types of data analysis used in business decision-making include: descriptive, diagnostic, predictive, prescriptive.

Descriptive analysis focuses on summarizing historical data to understand what has happened in the past. It includes techniques like reporting, data visualization, and dashboards. Diagnostic analysis aims to determine why something happened by examining data to identify patterns and relationships. It often involves drill-down, data discovery, and correlations. Predictive analysis uses historical data to predict future outcomes. It includes techniques such as regression analysis, forecasting, and machine learning models. Prescriptive analysis suggests actions to achieve desired outcomes by analyzing data and predicting future trends. It involves optimization and simulation techniques to recommend the best course of action.

The research proposes a model that establishes the relationship between big data, artificial intelligence, and the type of data analysis. The model starts with the various forms of big data (structured, semi-structured, unstructured) that organizations generate. These different types of data require specific processing and analysis methods. The next layer involves applying AI techniques (data mining, machine learning, text mining, deep learning) to analyze big data. Each AI technique is suited to handling and extracting meaningful insights from different data structures. The final layer focuses on the analysis performed using AI techniques on big data. Descriptive and diagnostic analyses help understand past events and their causes. Predictive analysis helps forecast future events, while prescriptive analysis provides actionable recommendations.

Research Questions

RQ1: What are the types of artificial intelligence algorithms that companies require for the types of data analysis?

RQ2: What are the business reasons that require data analysis?

RQ3: What are the types of analysis actions that companies require?

Hypothesis

H_1: Big data types depend on artificial intelligence types.

H_2: The types of artificial intelligence depend on the types of data analysis

Methodology

This study uses the data published on the experiences of 3,574 employees from around the world related to the learning experience on AI and data analytics. The selected population includes male and female employees working in the United States of America, the United Kingdom, Canada, Germany, India, China, Russia, France, Brazil, and Australia. These participants worked as data scientists, software development engineers, data analysts, scientists, researchers, machine learning engineers, programmers, engineers, statisticians, computer scientists, predictive models, database engineers, data miners, and operation research practitioners. A text mining analysis was implemented, through NVIVO software, to establish the visual association between the types of Big data structures and the types of artificial intelligence, and between the types of artificial intelligence and the types of analysis. On the other hand, visualizations of big data and artificial intelligence were established that were implemented by data analysts, data scientists, programmers and researchers. A Dashboard was developed, through Tableau software, to represent the countries with analysts and data scientists in the research. A chi-square analysis, through Excel's mega stat software, to establish the relationship between big data and artificial intelligence, and the relationship between artificial intelligence and types of data analysis.

Results

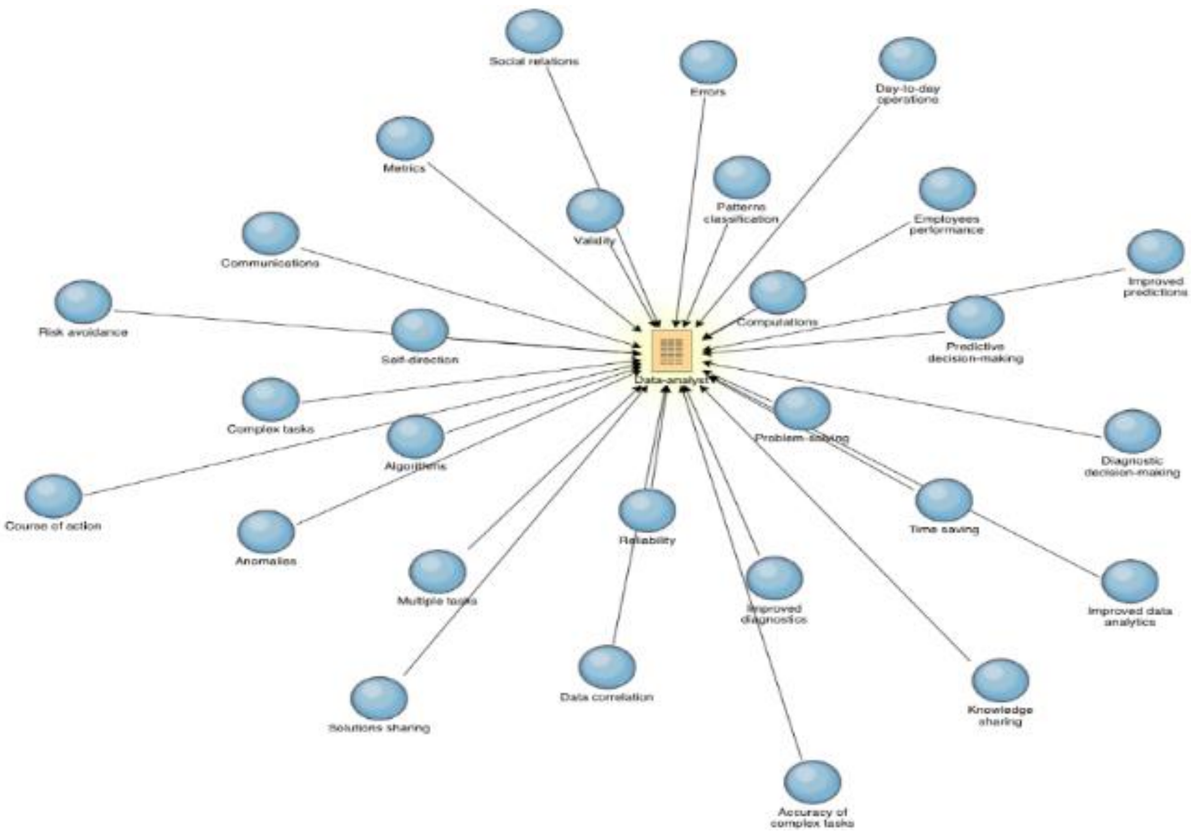

Figure 2: Association of Big Data and Artificial Intelligence with Data Analysis

Figure 2 illustrates the association of Big Data and Artificial Intelligence (AI) with Data Analysis, highlighting various factors and outcomes linked to this relationship. At the center of the figure is "Data Analysis," representing the core process that leverages Big Data and AI to extract insights and drive business decision-making. The surrounding nodes represent various factors and outcomes associated with integrating Big Data and AI in Data Analysis.

The model in Figure 2 demonstrates the complex and multifaceted relationship between Big Data, AI, and Data Analysis. It highlights how integrating Big Data and AI enhances various aspects of data analysis, leading to improved decision-making, operational efficiency, and overall organizational performance. The factors and outcomes surrounding the central node of Data Analysis illustrate the diverse benefits and applications of AI and Big Data in modern business environments, emphasizing their critical role in driving innovation and strategic decision-making.

Figure 3: Types of Artificial Intelligence Algorithms Implemented by Data Analysts and Scientists

Figure 3 presents a word cloud visualization of various artificial intelligence (AI) algorithms and techniques data analysts and scientists implement. Word clouds are a popular visualization method to display the frequency or importance of words within a dataset. In this case, the size of each term in the word cloud indicates its prevalence or significance in the context of AI algorithms used by professionals in the field. The presence of terms like "text processing," "natural language," "segmentation," and "ensemble" demonstrates the diverse range of AI techniques used by professionals. This variety reflects the multidisciplinary nature of data science and AI, incorporating methods from statistics, machine learning, natural language processing, and more. Support Vector Machines (SVMs), K-Nearest Neighbors (KNN), Gradient Boosting, and Convolutional Neural Networks (CNNs) are also mentioned, indicating the application of these well-known algorithms in various tasks.

The word cloud in Figure 3 provides an insightful overview of the AI algorithms and techniques frequently implemented by data analysts and scientists. The prominence of specific terms highlights critical methods and tools essential in data science, reflecting the complexity and diversity of approaches used to analyze and interpret large datasets. This visualization underscores the indispensable role of regression techniques, tree-based models, validation methods, and neural networks, among others, in the toolkit of modern data professionals.

Figure 4: Types of Artificial Intelligence Algorithms Implemented by Data Scientists

Figure 4 presents a word cloud visualization of various types of artificial intelligence (AI) algorithms and techniques implemented by data scientists. The size of each term in the word cloud indicates its frequency or significance in the context of AI algorithms used by professionals in this field. Random Forests, Neural Networks, Ensemble Methods, and Bayesian Techniques: These terms demonstrate the multidisciplinary nature of data science and AI, incorporating methods from various domains such as statistics, machine learning, and artificial intelligence. Although not prominently displayed, techniques like Principal Component Analysis (PCA) are implied. These techniques reduce the number of features in a dataset while preserving essential information. Terms like "time" suggest the importance of time series analysis in forecasting and trend analysis.

The word cloud in Figure 4 provides an insightful overview of the AI algorithms and techniques frequently implemented by data scientists. The prominence of specific terms highlights critical methods and tools essential in data science, reflecting the complexity and diversity of approaches used to analyze and interpret large datasets. This visualization underscores the crucial role of regression techniques, tree-based models, ensemble methods, and neural networks in the toolkits of modern data professionals. Additionally, the presence of Bayesian methods and support vector machines indicates the importance of probabilistic and classification techniques in handling various data science tasks. The figure illustrates the rich array of methodologies data scientists employ to derive insights and make informed decisions.

Figure 5: Types of Artificial Intelligence Algorithms Implemented by Data Scientists

Figure 5 presents a word cloud visualization of various data types and tasks associated with artificial intelligence (AI) algorithms implemented by data scientists. The size of each term in the word cloud indicates its frequency or importance in the context of AI applications used by professionals in this field. The word cloud in Figure 7 provides an insightful overview of the data types and tasks associated with AI algorithms implemented by data scientists. The prominence of terms like "relational," "video," "image," and "text" highlights the diverse data types handled by AI applications. Critical tasks such as product development, business optimization, and decision-making are also emphasized, showcasing the broad impact of AI across different domains. The visualization underscores the central role of machine learning in analyzing and learning from data and highlights the importance of building a strong data infrastructure to support these activities. Additionally, the terms "influence" and "understand" reflect AI's overarching goals of providing valuable insights and driving meaningful impact in various fields.

Figure 6: Types of Data Analysis Revealed by Data Analysts and Scientists

Figure 6 presents a word cloud visualization of various types of data analysis and related issues revealed by data analysts and scientists. The size of each term in the word cloud indicates its frequency or importance in the context of data analysis tasks and challenges faced by professionals in this field.

The word cloud in Figure 6 provides an insightful overview of the types of data analysis and related issues faced by data analysts and scientists. The prominence of terms like "organization," "lack," "dirty data," and "management" underscores the critical challenges related to data quality, resource availability, and effective data management. Core activities such as decision-making, financial analysis, and business strategy are highlighted, reflecting the broad impact of data analysis across various domains. Additionally, the visualization emphasizes the importance of collaborative efforts, adequate support systems, and addressing common barriers like data access, politics, and privacy concerns.

		Artificial Intelligence			
		1	**2**	**3**	Total
Big Data	**1**	988	165	183	1336
	2	2593	538	641	3772
	3	213	30	133	376
	4	2812	540	1092	4444
	Total	6606	1273	2049	9928

169.54	chi-square
6	df
5.6228E-34	p-value
16.877894	ChiSQ-Crit

Figure 7: Relationship Between Big Data and Artificial Intelligence

Figure 7 presents a contingency table showing the relationship between Big data and artificial intelligence (AI), along with the results of a Chi-square test to assess the significance of this relationship. The key findings and insights are the relationship between Big Data and AI, given that the contingency table and Chi-square test results reveal a significant relationship between different types of big data (structured, semi-structured, unstructured) and AI techniques (data mining, machine learning, text mining, deep learning). The Chi-square value (169.54) and the extremely low p-value (5.6228E-34) indicate a strong association between big data and artificial intelligence at a 99% confidence level. Another critical insight is that specific AI techniques are preferentially applied to particular big data structures. For example, structured data is primarily analyzed using data mining algorithms, reflecting the ease of processing well-organized datasets. Unstructured data, on the other hand, often requires advanced AI methods like deep learning and text mining due to its complexity.

This analysis suggests that specific types of Big data are more likely to be associated with AI techniques. For instance, categories with higher frequencies (such as Big Data Category 2 with AI Category 1) show a stronger association, indicating that certain AI methods are preferentially applied to specific types of Big Data. This relationship can help inform the strategic application of AI to Big Data in practical scenarios, optimizing the effectiveness of data analysis and decision-making processes.

		Types of Data Analysis				
		1	2	3	4	Total
Artificial Intelligence	1	2141	2316	1421	726	6604
	2	398	461	282	131	1272
	3	411	860	474	304	2049
	Total	2950	3637	2177	1161	9925

126.07	chi-square
6	df
8.61E-25	p-value
16.8119	ChiSQ-Crit

Figure 8: Relationship Between Artificial Intelligence and Types of Data Analysis

Figure 8 presents a contingency table showing the relationship between Artificial Intelligence (AI) and Types of Data Analysis, along with the results of a Chi-square test to assess the significance of this relationship.

On the other hand, another contingency table established the relationship between AI techniques and types of data analysis (descriptive, diagnostic, predictive, and prescriptive). The significant Chi-square value (126.07) and low p-value (8.61E-25) indicate a strong association between artificial intelligence and types of data analysis. AI methods are tailored to specific data analysis needs. Predictive and prescriptive analyses rely heavily on advanced machine learning and deep learning algorithms to make accurate forecasts and provide actionable recommendations. Conversely, descriptive and diagnostic analyses often use more straightforward data mining techniques to summarize historical data and identify patterns.

The results highlight how different AI methods are tailored to various data analysis needs, optimizing their effectiveness in extracting insights and informing decision-making processes. This understanding can guide organizations in selecting the appropriate AI techniques based on the specific type of data analysis required.

Discussion

The research findings reveal that the data analysis that companies develop is associated with metrics, social relations, patters, classification, day to day operations, computations, employee's performance, predictive decision-making, improved predictions, problem solving, time saving, diagnostic decision-making, improved data analytics, knowledge sharing, improved diagnostics, accuracy of complex tasks, data correlation, solutions sharing, multiple tasks, anomalies, algorithmics, course of action, complex tasks, direction, risk avoidance and communication. Findings show that companies' database specialists carry out the following actions: Unknown facts, accurate predictions, accurate of complex tasks, time saving, predictive decision-making, improve diagnostics, improved predictions, employee's performance, knowledge sharing, patters classification, descriptive decision-making, errors, computations, algorithms, reliability, validity, managerial tasks, data analytics, and problem-solving.

The results showed that the most frequent types of algorithms implemented by data analysts are visualization, data cross, logistic analysis, decision forests, random analysis, processing language, clustering analysis, network Bayesian, and simulation. The reasons that justify the types of analysis that companies require are: organizational, data lack, financial, direction company, talent support and management team, among others. The research findings indicate that the types of data that companies analyze in order of greatest frequency are: relational data, image, text and video.

The findings suggest that Big Data and Artificial Intelligence (AI) with Data Analysis, leading to improved decision-making, operational efficiency, and overall organizational performance. Big data and AI are integral to the role of database engineers, can enhance predictive and diagnostic capabilities, improve accuracy and efficiency in complex tasks, facilitate better communication and knowledge sharing within the organization. The association between Big data, artificial intelligence, and programmers, enhance software development processes for programmers by providing advanced tools for data aggregation, pattern classification, and predictive analysis. Types of artificial intelligence algorithms implemented by data analysts and scientists, incorporate methods from statistics, visualizations, machine learning, natural language processing, support vector machines (SVMs), K-Nearest Neighbors (KNN), Gradient Boosting, and Convolutional Neural Networks (CNNs). Types of artificial intelligence (AI) algorithms and techniques implemented by data scientists, incorporate methods from logistic regression, decision trees, random forests, Bayesian networks, and neural networks.

The findings indicate that AI aids business managers in performing accurate diagnostic analytics by emphasizing deep learning and machine learning over data mining. AI tools reviewed include Gradient Boosted Machines, Ensemble Methods, Random Forests, Markov Logic Networks, Support Vector Machines, Association Rules, Cross-Validation, KNN and Other Clustering, Natural Language Processing, Convolutional Neural Networks, Generative Adversarial Networks, Evolutionary Approaches, and Recurrent Neural Networks.

The findings indicate that for the descriptive analysis AI supports managers by focusing primarily on machine learning tools, such as Gradient Boosted Machines, Ensemble Methods, Random Forests, Markov Logic Networks, Support Vector Machines, Association Rules, Cross-Validation, KNN and Other Clustering, and Natural Language Processing. In predictive analytics, AI emphasizes data mining and deep learning tools over machine learning. These include Bayesian Techniques, Regression, Hidden Markov Models, Logistic Regression, Decision Trees, and Neural Networks. For prescriptive analytics, AI supports managers by concentrating on machine learning tools like Gradient Boosted Machines, Ensemble Methods, Random Forests, Markov Logic Networks, Support Vector Machines, Association Rules, Cross-Validation, KNN and Other Clustering, and Natural Language Processing.

The study shows that there is a significant dependency between the types of big data and the types of AI, as well as a dependency between the types of artificial intelligence and the types of data analysis. The results highlight the ways in which AI methods for processing big data and types of data analysis are connected. This insight leads to organizational efficiency as it allows the deployment of the right AI tools. Specifically, 66% of AI algorithms for data mining were used for structured data, analyzing 37% of diagnostic data types. Only 3% of prescriptive data types were analyzed using text-mining AI algorithms.

Artificial intelligence (AI) plays a crucial role in data analysis for business. AI tools process data much faster than humans, speeding up decision-making and can suggest alternatives and search for specific commands in data analysis libraries. AI detects inconsistencies in data and can flag errors before they occur. This guarantees more accurate and reliable results. Using natural language processing (NLP), AI chatbots allow non-technical users to analyze large data sets without mastering scientific jargon. AI automates the creation of reports, saving companies time and resources. AI algorithms help process large volumes of data, discover patterns, and make informed decisions.

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